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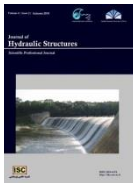

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Development of a new hybrid technique for estimating of relative uplift force in gravity dams based on whale optimization algorithm

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Abstract

A numerical model is developed in this study using finite element method (FEM) to estimate relative total uplift force for different positions of holes of drainage gallery in the foundation of Guangzhao gravity dam, located in China. The data of the relative total uplift force generated for different input combinations using FEM were used to develop machine learning (ML) models. A three-layer Artificial Neural Network (ANN) and a new hybrid model known as ANN-Whale Optimization Algorithm (ANN-WOA) were used for this purpose. The results showed that R^2, RMSE, NSE, KGE and RE% for ANN-WOA model in estimation of the relative total uplift forces were 0.998, 0.021, 0.989, 0.964 and 3.3% respectively and those for ANN model were 0.980, 0.023, 0.982, 0.953 and 4.67% respectively, which indicate the higher accuracy of ANN-WOA model compared to ANN model. The new hybrid model, ANN-WOA with the less RMSE and RE% and high KGE and NSE is a more appropriate model for the estimation of the relative total uplift force. The extracted metrics of violin plots indicated that the probability distribution of the relative total uplift force estimated using ANN-WOA model was very similar to that obtained using FEM.

Keywords: Gravity dam; Uplift force; Finite element method; Hybrid artificial neural network-whale optimization algorithm.

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1. Introduction

Seepage from the dams and the resulting increase in uplift force is considered as one of the most important factors for the destruction of dams. The dams and other hydraulic structures associated with water storage are always subjected to water seepage from the foundation, sides and sometimes their bodies. The upward force exerted from the bottom of the dam due to water seepage through the dam foundation is referred as uplift force. The uplift force sometimes becomes high enough to overturn the dam. Therefore, it is very important to make logistics in design in order to reduce the amount of uplift force. This is usually done by installing a drainage gallery in the dam body where drainage wells are used to collect seepage water from the body of the dam, especially from the dam foundation to reduce uplift forces.

The optimum design of the drainage system is decided through numerical analysis [1]. Traditionally, a closed-form (analytical) solution based on seepage theory is used to determine the optimal location of drainage gallery system of gravity dams to keep the uplift force minimum [2].

Salmasi et al. [3] carried out a numerical simulation to measure the effect of relief wells for decreasing uplift in a homogeneous earth dam. Relief wells are used extensively to relieve excess hydrostatic pressure in pervious foundation strata overlain by impervious top strata, conditions which often exist landward of levees and downstream of dams and hydraulic structures. Results showed that by decreasing the distance between relief wells and increasing the diameter of the relief wells, total uplift pressure decreases.

The optimum location of the drainage system is not fixed and therefore, different arrangements of drain system are numerically solved to find the optimum design of drainage system for the reduction of uplift forces (Nourani et al. [4], Salmasi et al. [5]). Salmasi and Nouri [6] examined the influence of upstream semi-impervious blanket of earth dams on seepage. The reduction of seepage can also decline the uplift force under the dam. The examination produces adequate data for common place 2D embankment dam cross-sections by numerically solving a varied range of arrangements of a provision of upstream blanket. Results indicated that application of impervious of blanket in upstream of the earth dam at accurate length and thickness is effective in decreasing seepage and subsequently increasing dam stability. Jafari et al. [7] used granular filter below the bed of a canal to decline uplift force. They applied numerical investigation with finite element method. Results show that utilize of a filter envelope nearby the drain-pipe for declining hydro-static pressure can be beneficial.

The capacity of Machine learning (ML) models have been implemented successfully in the field of geo-science and related hydraulic structure problems (Khosravinia et al. [8], Khozani et al. [9]; Maroufpoor et al. [10], Mohammed et al. [11], Sharafati et al.[12], Daneshfaraz et al. [13]). In particular, the ML model have been used in recent years for the modelling of drainage system (Chinh et al. [14], Baghalian and Nazari, [15], Al-Suhaili and Karim, [16], and Nourani et al. [17]). Chinh et al. [14] used a feed-forward artificial neural network (ANN) to model water levels in drainage canals in order to study the relations between rainfall and water table of a drainage canal in flat and low-lying in an agricultural region. Khan et al. [18] used the ANN to model seepage of a channel to analyze the variation of channel seepage using electromagnetic imaging (EM31) data, hydraulic conductivity, and the depth and salinity of groundwater. Baghalian and Nazari, [15] estimated the uplift pressure below a diversion dam using ANN and Genetic Algorithm (GA), where the Laplace’s equation was used to solve for piezometric heads and uplift pressures. Al-Suhaili and Karim [16] studied the performance of a GA method together with ANN technique to discover the optimal values of upstream and downstream cut-off lengths, apron length and the required downstream protection length for hydraulic structures to satisfy a safety factor in term of uplift pressure and piping failures.

Sattar [19] used 140 data from large dams' failure information to predict breach condition based on gene expression programming (GEP). These data are related to earth-fill and rock-fill embankments from the world. Dam parameters include geometry, hydraulic and geography information. A new empirical formula was presented using the GEP. Nourani et al. [17] applied ANN method to predict output hydrograph from the breach in earthen dams using laboratory and field data from breaches. They showed that soil cohesiveness and angle of friction are two important properties in breach development. In addition, ANN was in good agreement with the observed values. Sharghi et al. [20] conducted an ensemble artificial intelligence (AI) based model to predict seepage from Sattarkhan earth-fill dam, Iran. The results revealed that the assembling technique could enhance the AI modelling by up to 20% in the verification stage. Choi et al. [21] used the ANN to estimate the scour depth nearby bridge piers. The database was from field-scale scour depth reports. It was presented that data quality evaluation such as the Euclidean distance strategy and the Mahalanobis distance strategy significantly develops the forecast of the ANN model. One of the newest samples of meta-heuristic algorithms, that has not yet been generally explored, is the Whale optimization algorithm (WOA), accessible by Mirjalili and Lewis [22]. Du et al. [23] used the WOA as an optimizer in earlier investigations in electrical power forecasting. Although, several research evidence the potential of the AI models for solving diverse hydraulic engineering problems, the associated problem of the hyper-parameters optimization is still the major drawback that needs the scholars attention to solve (Yaseen et al. [24, 25]). Samadianfard et al. [26] evaluated the ability of MLP hybrid models with WOA and GA in predicting wind speed. Various indicators were used to evaluate their performance and finally it was determined that the MLP model with WOA (MLP-WOA) has more accurate results than MLP-GA. Tuning AI models with reliable optimization algorithms is still ongoing research era of computer aid simulation [27].

Regarding the aforementioned studies, we can conclude that the estimation of the uplift force under dams or other hydraulic structures has not been considered with application intelligence or hybrid intelligence methods. To the best knowledge of the current research, a novel hybrid model known as Artificial Neural Network-Whale Optimization Algorithm (ANN-WOA) is used in this study for the estimation of uplift force in a gravity dam. The Guangzhao gravity dam, located in China was used as the case study. The finite element method (FEM) was used to simulation and estimation the uplift force for different positions of drainage holes in the foundation of the gravity dam. Obtained data using FEM namely, the relative total uplift force for different diameters of drains holes, their locations from the dam heel and the distance center-to-center of drain holes were used for the development of ANN-WOA model. The most goals of the present study are examining and analyzing the accurateness of an enhanced artificial neural network (ANN) model utilizing the whale optimization algorithm (WOA); where the main purpose of the WOA is to specify the optimum parameters of the ANN model. As a results, the first target in current study is numerical simulation with finite element method (FEM) that was used to estimate the uplift force for different configurations of vertical drain holes of drainage gallery in the gravity dam. The second target of the current study is the estimation and sensitivity analysis of the relative uplift force obtained from FEM using artificial intelligence. In this study used from a novel hybrid optimization tool, namely whale optimization algorithm (WOA), for finding the most appropriate parameters of the ANN model for estimating the relative uplift force. Therefore, a novel hybrid technique, hybrid neural network with whale optimization algorithm is called ANN-WOA, is developed and has been used as intelligence estimating model. Also the performance of ANN-WOA model was compared with ANN, FEM (by using of

SEEP/W software) and Analytical method in estimation of total uplift force. This is the first application of ANN-WOA in the calculation of the uplift force in gravity dams. It is expected that the novel technique presented in this study will help in exact estimation of uplift force in a gravity dam for better and cost-effective management of dam safety.

2. Materials and Methodology
2.1. Governing Equations

The common equation of flow in porous media can be presented using Darcy's equation. When Darcy’s equation is combined with the continuity equation of flow and converted to Richard's equation, it becomes a partial differential equation that describes seepage flow. The common differential equation of seepage flow for two-dimensional (2D) state can be stated as:

$$\frac{\partial}{\partial x}\left(k_x \frac{\partial h}{\partial x}\right) + \frac{\partial}{\partial y}\left(k_y \frac{\partial h}{\partial y}\right) + Q = \frac{\partial \theta}{\partial t} \quad (1)$$

where h is the total head (m) that is equal to Z+H and in that Z and H are static and pressure head respectively, Q is the applied boundary flux (1/s), θ is the water content in volumetric form (m^3/m^3), k_x and k_y are the hydraulic conductivities in x and y-directions (m/s), and t is time (s). The Eq.1 for steady state condition can be expressed as follows:

$$\frac{\partial}{\partial x}\left(k_x \frac{\partial h}{\partial x}\right) + \frac{\partial}{\partial y}\left(k_y \frac{\partial h}{\partial y}\right) + Q = 0 \quad (2)$$

If the porous media is homogeneous and isotropic ($k_x = k_y = k$) and the seepage flow is zero (Q=0), Eq.2 can be simplified in the form of Eq. 3, which is known as the Laplace equation:

$$\frac{\partial^2 h}{\partial x^2} + \frac{\partial^2 h}{\partial y^2} = 0 \Rightarrow \nabla^2 h = 0 \quad (3)$$

The SEEP/W software was used in this study to solve the differential equation for identified boundary conditions using the FEM [28].

2.2 Numerical Simulation using Finite Element Method (FEM)

A gravity dam namely Guangzhao gravity dam, located in China with the dimensions as shown in Fig.1 was considered in this study for numerical simulation as the case study [1]. The width of the floor (L) and the length (T) of the dam are 125 and 30 meters respectively.

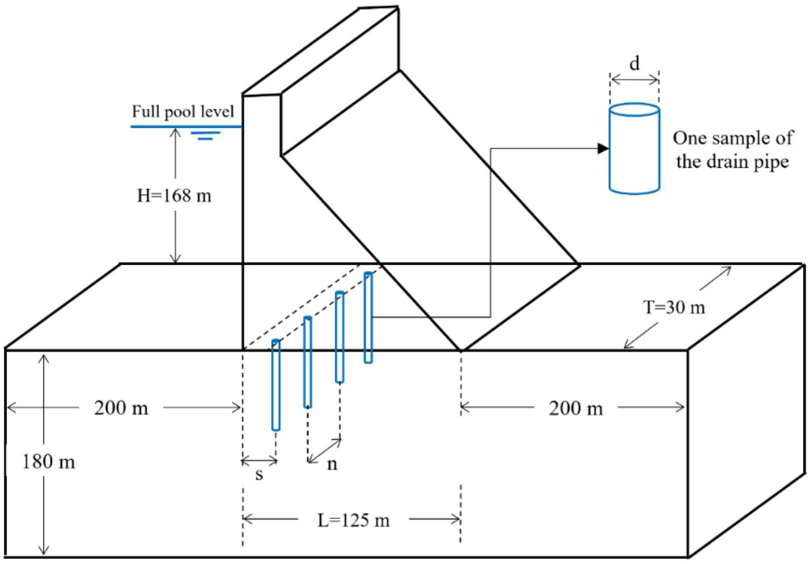

Figure 1. Illustration of the drain-hole row of drainage gallery system in the gravity dam section

The uplift force in gravity dams is a function of the vertical drains of the drainage gallery. The effective factors are the diameter of the drain (d=2r, r is radius of drain holes in drainage gallery), the center-to-center distance of the drains (n), the distance of drain row from the heel of the dam (s), and water surface level of the reservoir (H). The simulation was conducted for the foundation of gravity dam without drainage gallery and 12 arrangements of vertical drains inside the drainage gallery having different diameters (d), 0.05, 0.10 and 0.15 meters, each of which in 4 modes of distance (n), 3, 4, 5 and 6 meters. The impact of the drain row distance from the heel of dam was also simulated. For this purpose, 12 different distances of drain row from upstream of the dam were considered, 0, 5, 10, 15, 20, 25, 30, 40, 60, 80, 100 and 125 meters. The aforementioned conditions were used for two states of water surface level (H) in the upstream of the reservoir namely, 168 and 130 m. Thus, the effect of water surface level of the reservoir also was investigated. Figure 1 indices a schematic view of the location of the drains in the drainage gallery and the parameters used in this study. Depending on the conditions used in the present study, the plan view model of the SEEP/W software was used to simulate the dam foundation along with the vertical drainages. Figure 2 demonstrations the plan-view of dam foundation in software media where s, d, n and H are 10, 0. 15, 6 and 130 meters, respectively.

For numerical simulation, the boundary conditions (BC) at the upstream and downstream the gravity dam foundation were considered equal to the water surface level in the pool and tail water level in the form of a pressure head respectively. The upstream water surface level was considered to vary between 168 and 130 meters, while the water level in the downstream was considered zero. Therefore, the pressure heads in the upstream were considered as 168 and130 meters as the boundary condition. The boundary condition at the vertical drains was considered as zero pressure. Since all the analyses were conducted for a steady state condition, volumetric water content was not considered. The foundation of dam material according to the characteristics Guangzhao gravity dam is deliberated to be homogeneous and isotropic with a saturated permeability of Ksat=2.7E-07 m/s (Fig. 2) [1].

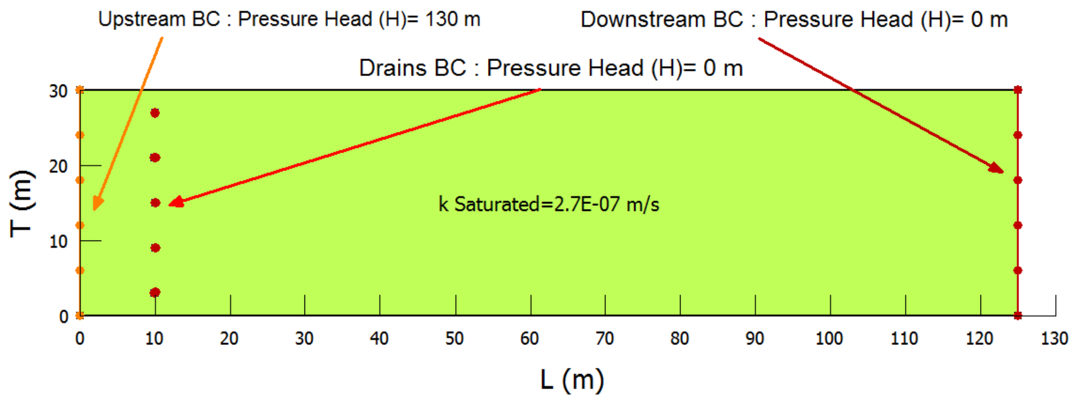

Figure 2. Plan view of dam foundation with 5 drains for specified boundary conditions (s=10 m, d=0.15 m, n=6 m, H=130 m)

An independence test of mesh was implemented to specify the optimum number of elements in the mesh required for the development of the numerical model. For this objective, the percent of relative error (RE %) was obtained for the different number of elements. It should be noted that the basis of the calculation in estimating the RE% is based on comparing numerical simulation results with results of Chawla et al. (1990) in determining the uplift pressure in a specific location and similar conditions. The result showed (Fig. 3) that the RE% was nearly fixed when the elements number was ≅30,000. Hence, the average element size of 30,000 was used in this study. It should be noted that the number of elements varies slightly with the changes in the diameter of drains. Figure 4 illustrates the mesh properties (number of elements and nodes) for the gravity dam foundation for s, d and n equal to 30, 0. 15 and 6 meters, respectively. Finite element mesh used to represent gravity dam foundation configuration is shown in the figure 4. The zoomed view of finite elements surrounding a drain is also shown in the figure 4 for clarity.

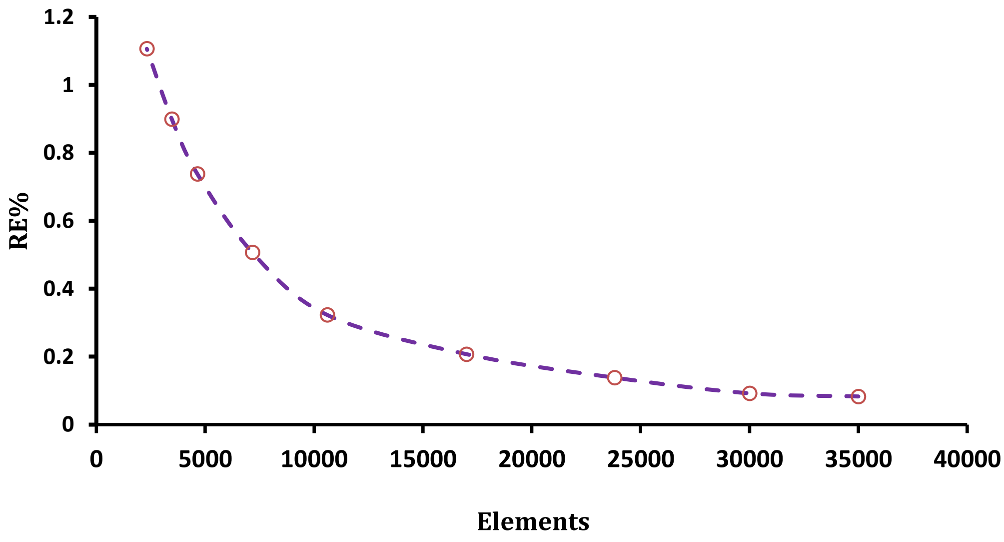

Figure 3. The RE% for different number of elements

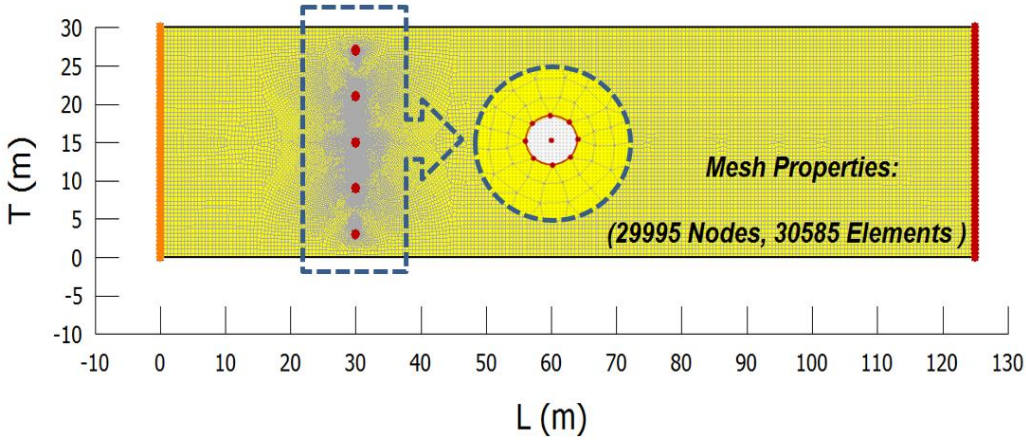

Figure 4. Finite element mesh used to represent gravity dam foundation configuration and zoomed view of elements surrounding a drain

2.3. Artificial Neural Network (ANN)

An artificial neural network (ANN) is a distributed parallel information processing system that resembles the biological neural networks in the human brain, and can be used for storing and recalling data, pattern classification, mapping input patterns to output algorithms, and grouping similar patterns [31]. The ANN follow two types of learning processes: supervised and unsupervised learning. In supervised learning, the network learns by comparing the predicted output with the known output. In unsupervised learning, the network does not need a known output for comparison and adjusts the strength of connections through repeated learning algorithm cycles. The multilayer perceptron (MLP) is the most common type of neural network used for supervised learning and widely employed for modeling complex nonlinear processes [32, 33]. This study evaluates the application of neural networks for estimating relative total uplift force of gravity dams. The MLP network consists of an input layer, an output layer, and one or more hidden layers containing weights that are typically determined through system training. The hidden layer adds up weighted inputs and uses an activation function to generate an output value. Figure 5 shows a three-layered ANN used in this study which is composed of (i) input layer, (ii) hidden layer, and (iii) output layer. The independent parameters in the input layer comprise: s/L, n/L, d/L and H/L, and the dependent variable is U_d/U_o. The optimum network architecture was defined as 4-8-1 which include 4 neurons for input, a single hidden layer with 8 neurons and 1 output neuron. The sigmoid tangent function for the input layer and the linear function for the output layer was selected for optimum performance of the model using the Lewenberg Marquard Algorithm (LMA) after 50 iterations.

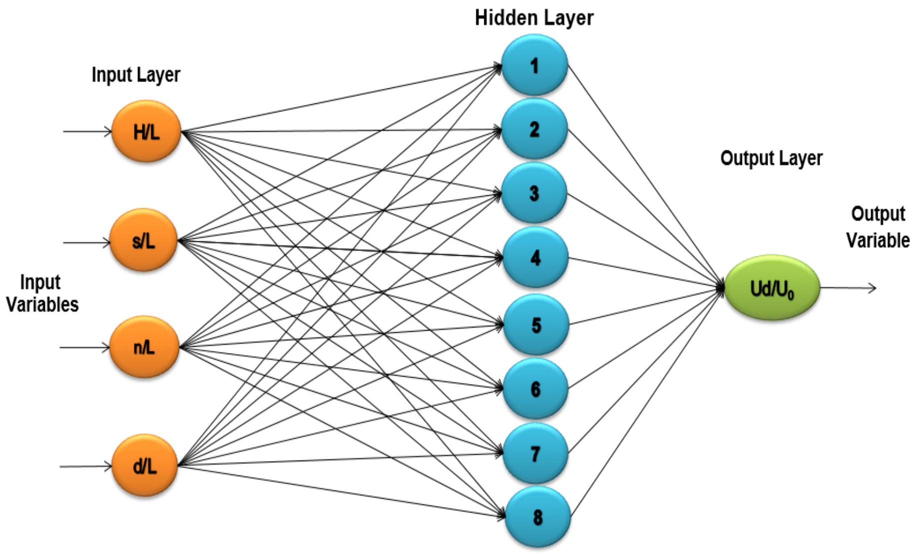

Figure 5. The architecture of artificial neural network used in this study

2.4 Whale Optimization Algorithm (WOA)

This algorithm is a meta-heuristic optimization process. This algorithm is inspired by humpback whales and was proposed by Mirjalili and Lewis [22] as a meta-heuristic optimization process. In fact, this method is a population-based algorithm based on the unique pattern of whales for catching more fish. The most interesting fact about hunting whales is their unique method called bubble net feeding. In this method, wales swirl around a group of fish and produce distinctive bubbles to trap the fish, causing them to move towards the water surface. They then move towards the fish and hunt them down using this technique (Fig. 6).

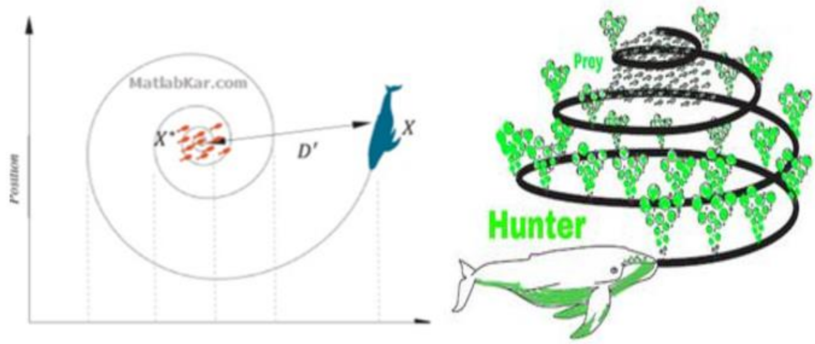

Figure 6. The basic concept of whale optimization algorithm (WOA)

Both artificial neural network (ANN) and hybrid it with whale optimization algorithm (ANN-WOA) were used to estimate the relative total uplift force (U_d/U_o) of gravity dam using four variables, H/L, d/L, n/L and s/L as input. To achieve this purpose, the data generated by numerical method has been used. The necessary steps to extract data in the numerical model include drawing the geometry of the foundation of the concrete dam, defining the materials properties (hydraulic conductivity), meshing, boundary conditions for each of the states, which after verification with an existing analytical method have used for the development of single and hybrid machine learning models. A total of 288 datasets were generated using FEM, of which

70% of the data (200 data) was applied for the training and the rest 30% (88 data) was applied for the testing of the models. A code was written in the *Wolfram Mathematica* software to select data randomly for training and testing for different runs. Finally, the desired model was selected based on the determination coefficient (R^2) and the root mean square error (RMSE). After 50 repetitions, the best conditions in term of R^2 and RMSE were found (R^2 = 0.995 and RMSE = 0.0223). After selection of best combination for dataset an artificial neural network (ANN) with the Whale Optimization Algorithm (WOA) was used to create novel method (ANN-WOA). The approach used for the development of ANN and ANN-WOA methods is revealed in Fig.7.

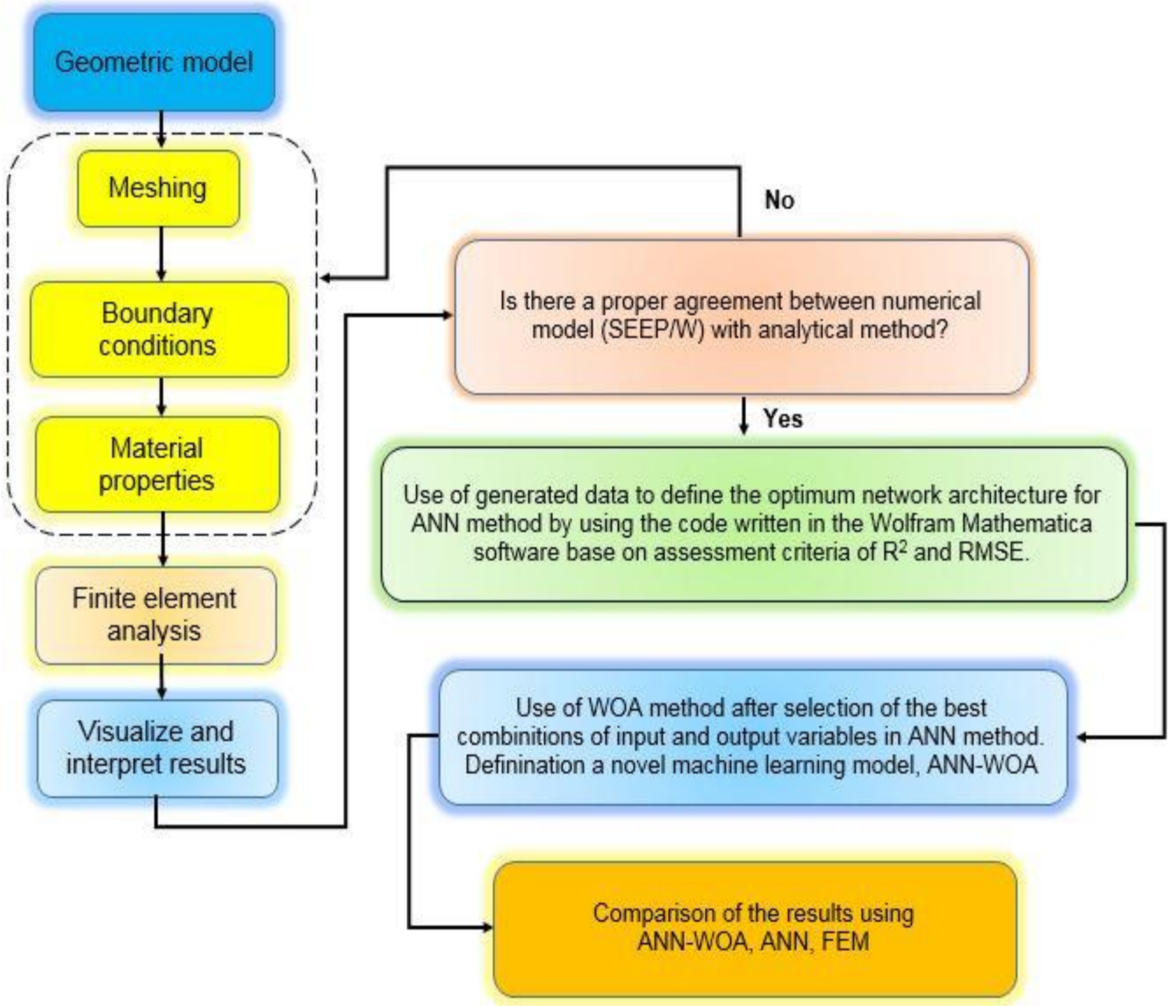

Figure 7. The methodology used for the development of new hybrid model

2.5 Model Performance Assessment

In this research, five statistical metrics namely, determination coefficient (R^2), root mean square errors (RMSE), percent relative error (RE%) [32], Nash-Sutcliffe efficiency (NSE), and Kling-Gupta efficiency (KGE) in order to investigation the accuracy of models, were used [30, 31] . The metrics are defined in Eqs.11-15 (Table.1). The assessment criteria of a model based on NSE and KGE are also given in the table.

Table 1. Statistica criteria applied in this study

Statistica Criteria	Value	Inference	Eq.
$R^2=\frac{\left[\sum_{i=1}^{N}\left(O_i-\bar{O}\right)\left(P_i-\bar{P}\right)\right]^2}{\sum_{i=1}^{N}\left(O_i-\bar{O}\right)^2\sum_{i=1}^{N}\left(P_i-\bar{P}\right)^2}$			(11)
$RMSE=\sqrt{\frac{\sum_{i=1}^{N}\left(P_i-O_i\right)^2}{N}}$			(12)
$RE\%=\frac{\sum_{i}^{N}\lvert P_i-O_i\rvert}{\sum_{i}^{n}P_i}$			(13)
$NSE=1-\frac{\sum_{i=1}^{N}\left(P_i-O_i\right)^2}{\sum_{i=1}^{n}\left(O_i-\bar{O}\right)^2}$	$0.75<NSE<1.00$ $0.65<NSE<0.75$ $0.5<NSE\le 0.65$ $0.4<NSE\le 0.5$ $NSE\le 0.4$	Very good Good Satisfactory Acceptable Unsatisfactory	(14)
$KGE=1-\sqrt{(R-1)^2+(\beta-1)^2+(\gamma-1)^2}$ $R=\frac{\left[\sum_{i=1}^{N}\left(O_i-\bar{O}\right)\left(P_i-\bar{P}\right)\right]}{\sqrt{\sum_{i=1}^{N}\left(O_i-\bar{O}\right)^2\sum_{i=1}^{N}\left(P_i-\bar{P}\right)^2}}$ $\beta=\frac{\overline{P}}{\overline{O}}\qquad \gamma=\frac{CV_P}{CV_O}=\frac{\frac{\sigma_P}{\overline{P}}}{\frac{\sigma_P}{\overline{O}}}$	$0.7<KGE<1.00$ $0.6<KGE<0.7$ $0.5<KGE\le 0.6$ $0.4<KGE\le 0.5$ $KGE\le 0.4$	Very good Good Satisfactory Acceptable Unsatisfactory	(15)

where O_i is the observed value (obtained from SEEP/W software), P_i is the estimated value of ANN and ANN-WOA models, $\bar{O}$ is the average of observed values, $\bar{P}$ is the average of estimated values, CVp is coefficient of variation of estimated values, CVo is coefficient of variation of observed values, σo is the standard deviation of observed values, σp is the standard deviation of estimated values and N is the data number.

3. Results and Discussion

3.1. Model Specification and Data Generation

The pore water pressure was calculated in each point in the porous medium of soil in dam foundation using FEM. Figure 8 shows the pressure head contours for flow lines and velocity vectors for s, d, n and H equal to 10, 0. 10, 6 and 130 meters, respectively. Pressure head contours change from 168 m at the dam upstream to the zero in the vertical drain position. This is because the collected seeped waters enter into drain and then is discharged to atmosphere.

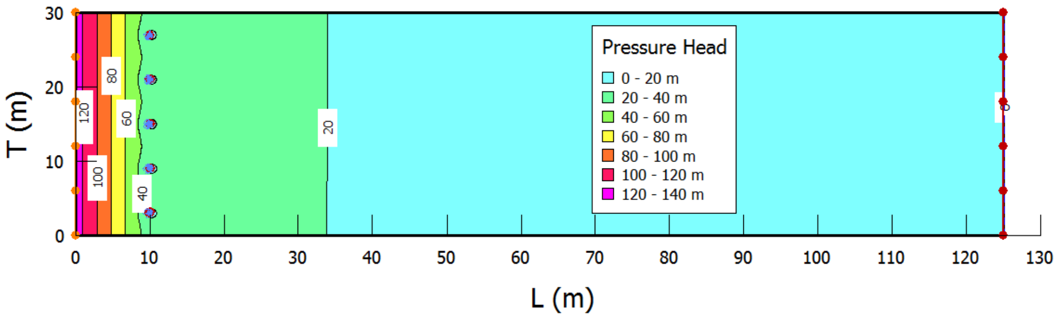

Figure 8. Pressure headlines at the foundation of the gravity dam with vertical drain (for s=10 m, d=0.015 m, n=6 m, H=130 m)

The values of H_d/H against the values of s/L for d/L = 0.0004, H/L=1.344, and n/L=0.048, 0.040, 0.032 and 0.024 is illustrated in Figure 9. The Figure 9 shows relative pressure head (H_d/H) decreases with the decrease of n/L or increase of d/L. In fact, a compressed effects of five essential parameters, i.e. H_d, H, s, L and d are showed in Fig. 9 that can be helpful in design considerations. This is accomplished using dimensionless parameters.

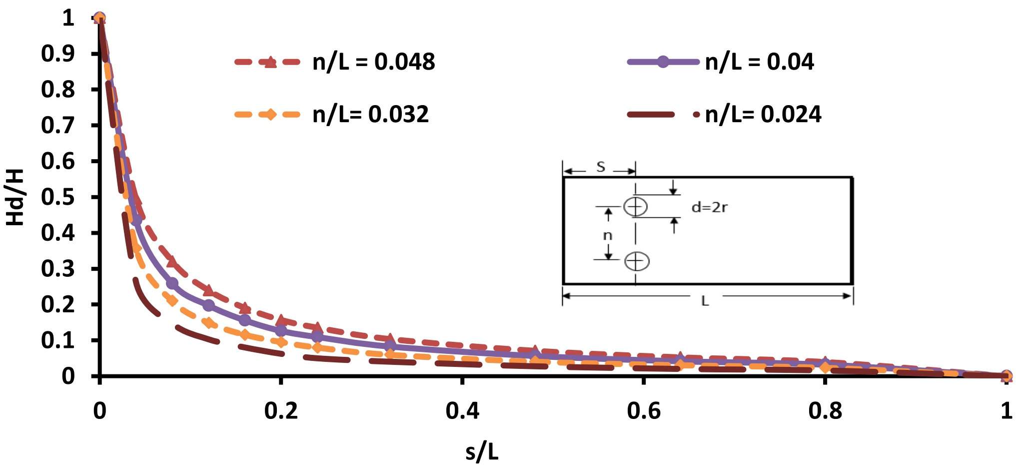

Figure 9. Changes in H_d/H with s/L for d/L=0.0004 and H/L=1.344

The changes in U_d/U_o with the changes in s/L for d/L = 0.0004, H/L=1.344, n/L=0.048, 0.040, 0.032 and 0.024 are illustrated in Figure 10. The Figure 10 shows that relative uplift force (U_d/U_o) decreases and then increases with the increase of s/L. It means that the optimum location drain system plays a significant role in the total uplift force. In design, it is necessary to obtain a minimum value for uplift force when using vertical drains for collection of infiltrated waters. This is because minimum uplift force, produces a dam design with higher stability against loads and also creates an economical design.

Table 2 shows the optimum values of s/L for H/L equals 1.344, and n/L=0.048,0.040, 0.032 and 0.024, and d/L=0.0004, 0.0008 and 0.0012 for which U_d/U_o is minimum. Table 2 indicates that for a constant upstream head, the effect of drains diameter is less than drains distance from each other (center-to-center) in the determination of the best position of the drains.

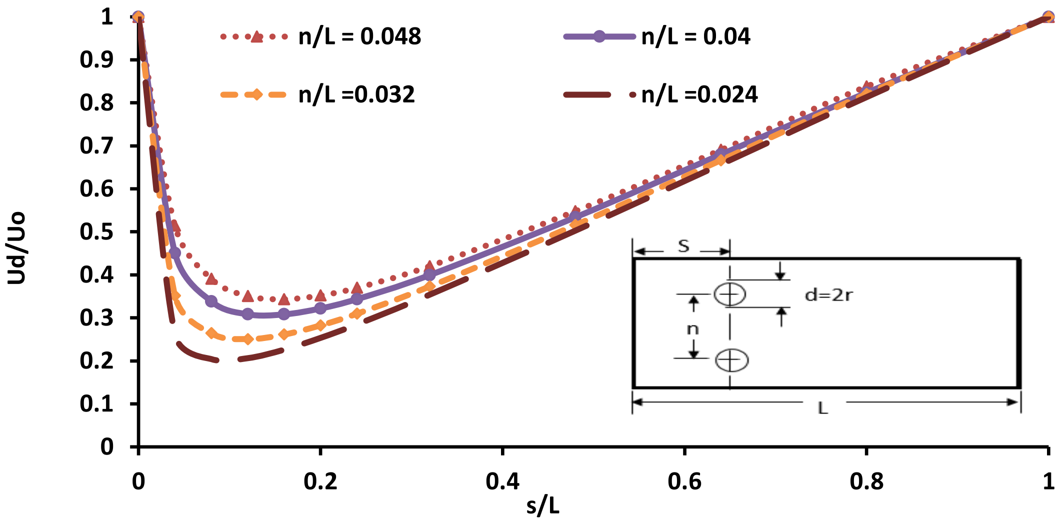

Figure 10. Variation of relative uplift force (Ud/Uo) with s/L for d/L=0.0004 and H/L=1.344

Table 2. Optimum location of vertical drains (s/L) for different values of d/L and n/L when H/L = 1.344

H/L=1.344			
$\frac{d}{L} = 0.0012$	$\frac{d}{L} = 0.0008$	$\frac{d}{L} = 0.0004$	
$\frac{s}{L}$	$\frac{s}{L}$	$\frac{s}{L}$	$\frac{n}{L}$
0.060	0.070	0.090	0.024
0.090	0.100	0.120	0.032
0.110	0.130	0.145	0.040
0.125	0.145	0.160	0.048

The results obtained in the present study using numerical simulations were validated with the results obtained by Chawla et al. [2] using analytical method for the same conditions. The variations of the relative total uplift forces with relative distance from the upstream of the dam estimated by Chawla et al. [2] and numerical simulations in the this research are shown in Fig. 11. A good agreement was observed between the results obtained from the two methods. It can be noted that analytical methods usually suffer from some simplifications in partial differential equations (PDE), but numerical modelling deletes these simplifications and solve full the PDE. For example, the complexity in analytical methods arise in soil heterogenic and soil anisotropic.

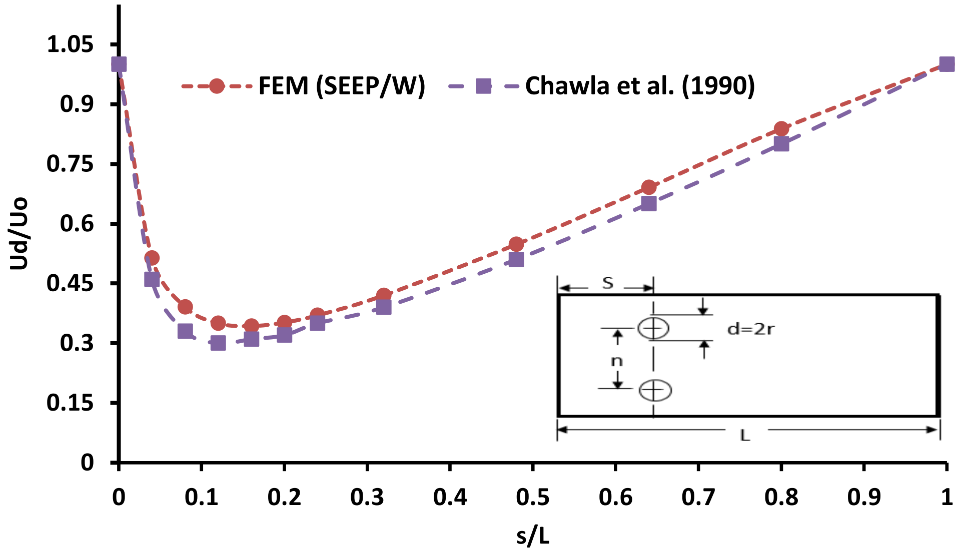

Figure 11. Comparison of variations of the relative total uplift forces with relative distance from the upstream of the dam estimated by Chawla et al. [2] and numerical simulations

The statistical summary of the input and output variables used in the training and testing phase of the models given in Table 3. The data for training and testing were selected for which the highest R^2 and the lowest RMSE were obtained. The statistics include minimum, maximum, mean, standard deviation and coefficient of variation.

Table 3. Statistical summary of the parameters during training and testing of models

	Training data					Testing data				
	$\frac{s}{L}$	$\frac{n}{L}$	$\frac{d}{L}$	$\frac{H}{L}$	$\frac{Ud}{Uo}$	$\frac{s}{L}$	$\frac{n}{L}$	$\frac{d}{L}$	$\frac{H}{L}$	$\frac{Ud}{Uo}$
Min	0	0.024	0.0004	1.04	0.162	0	0.024	0.0004	1.04	0.176
Max	1	0.048	0.0012	1.344	1	1	0.048	0.0012	1.344	1
Mean	0.0317	0.0318	0.0008	1.208	0.453	0.322	0.0301	0.0008	1.171	0.525
SD	0.272	0.0087	0.0032	0.151	0.243	0.306	0.0081	0.0032	0.151	0.287
CV=SD/Mean	0.858	0.273	0.0400	0.125	0.536	0.921	0.269	0.400	0.129	0.547

As mentioned earlier, several hydraulically parameters and dam geometric variables are affected uplift force beneath the dam foundation. In compressed or dimensionless form, these are d/L, s/L, n/L, H/L and U_d/U_o. Thus in the following, the application of ANN and ANN-WOA methods are provided for the first time in this study based on previous literature reviews.

The comparison of the observed and the estimated values of U_d/U_o, using ANN and ANN-WOA in testing phase is shown using scatter plots in Figs. 12 and 13, respectively. It can be seen from the linear line fit equations and R^2 values of the scatter plots that the ANN-WOA estimates were much closer to the observed values than the ANN estimates, which indicates better performance of ANN-WOA than ANN. The results also show that U_d/U_o can be estimated with high accuracy using ANN-WOA.

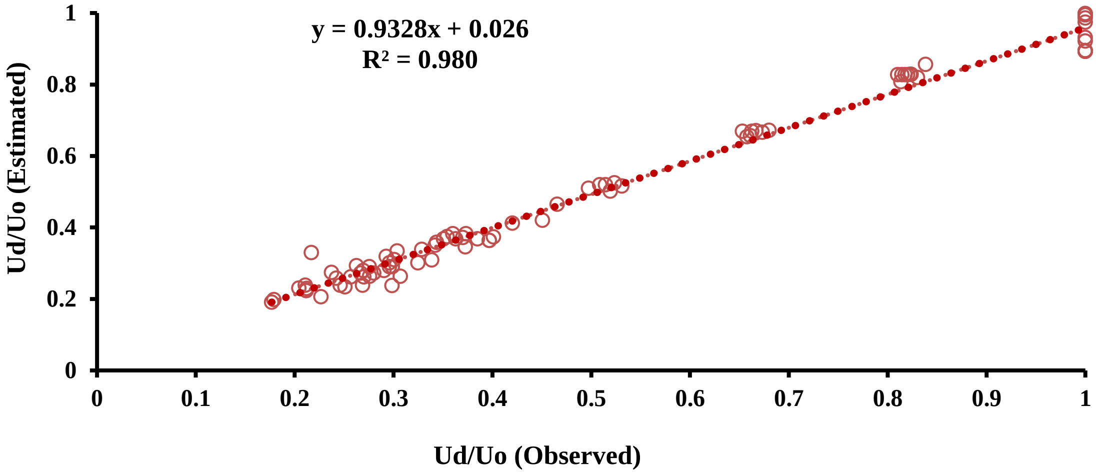

Figure 12. Scatter plot of observed and estimated relative uplift force during validation of ANN model

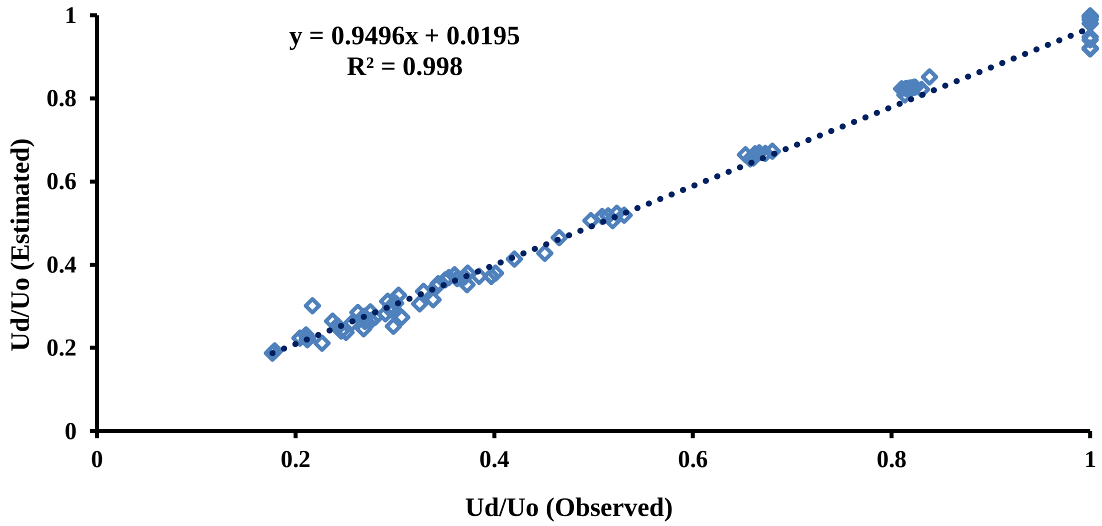

Figure 13. Scatter plot of observed and estimated relative uplift force during validation of ANN-WOA model

3.2 Diagnostic Analysis of Model Performance

The violin plot was also used to evaluate performance of models in estimating the values of the relative uplift force. Figure 14 indicates the violin plots for observed and estimated values of U_d/U_o using ANN and ANN-WOA models. Based on results of Figure 14, the relative uplift force estimated using ANN-WOA resembles more with the observed relative uplift force compared to that obtained using ANN. The 3rd (Q_3), 2nd (Q_2) and 1st (Q_1) quartiles along with maximum and minimum values for both developed models in order to comparison with observation mode are presented in Table 4, which indicates much similarities of ANN-WOA estimates with the observed data compared to ANN estimates.

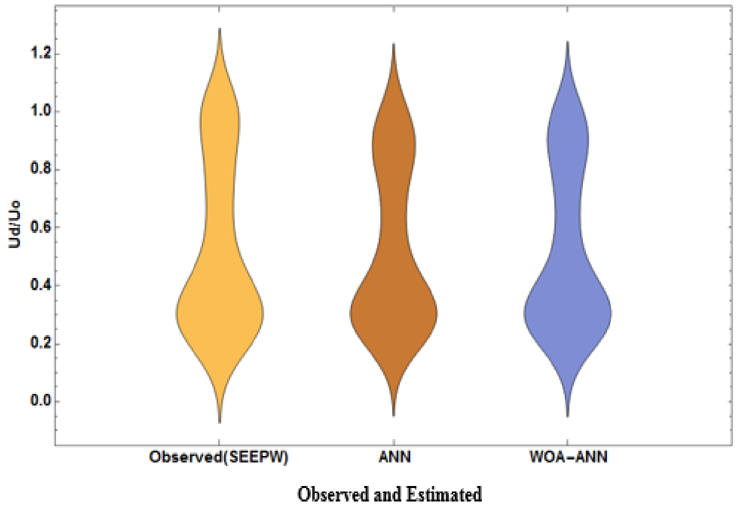

Figure (14) Violin plots of observed and estimated relative total uplift force using ANN and ANN-WOA during model validation

Table 4. Comparison the maximum, Q_3, Q_2, Q_1 and minimum values of the numerically estimated of observed relative uplift force, ANN and ANN-WOA estimated

	FEM (SEEP/W)	ANN	ANN-WOA
Maximum	1	0.998	0.998
Q_3	0.814	0.827	0.823
Q_2	0.380	0.372	0.372
Q_1	0.279	0.285	0.280
Minimum	0.175	0.190	0.187

The statistical metrics (R^2, RMSE, NSE, KGE and RE%) in the estimation of relative uplift force during training and testing of ANN and ANN-WOA models are given in Table 5. The ANN-WOA was found to perform better compared to ANN in term of all statistical metrics. Therefore, it can be remarked that ANN-WOA model estimates very near results to that achieved using the finite element method in estimating U_d/U_o.

Table 5. Statistical metrics obtained during training and testing of ANN-WOA and ANN models

	Testing data					Training data				
	R^2	RMSE	RE%	NSE*	KGE*	R^2	RMSE	RE%	NSE*	KGE*
ANN	0.980	0.023	4.67	0.982	0.953	0.994	0.023	3.4	0.990	0.989
ANN-WOA	0.998	0.021	3.50	0.989	0.964	0.991	0.017	2.6	0.994	0.990

* NSE and KGE indicate a very good performance of both models.

3.3 Sensitivity Analysis

To investigate the effect of input variables (d/L, s/L, n/L, and H/L) on U_d/U_o, the R^2 and RMSE for different combinations of input variables were investigated. The results obtained using five different models developed using different combinations of inputs are presented in Table 6. The results indicate that the accuracy of the optimal the ANN method decreased when s/L was eliminated from input combination which indicates s/L (the ratio of the distance of the drains from the dam upstream with respect to the width of the dam foundation) is the most sensitive parameter in determining the uplift force in gravity dams. The best performance

(R^2=0.9961 and RMSE=0.0247) was obtained when H/L was eliminated from the input combination. Therefore, it can be remarked that the uplift force in gravity dam can be better estimated using AI models with three input variables namely, s/L, n/L and d/L.

Table 6. Effect of various computations of inputs on the accuracy of ANN in the estimation of Ud/Uo

		ANN (Testing)	
Model	Input variables	R^2	RMSE
1	All	0.9550	0.0223
2	Eliminate s/L	0.0987	0.2508
3	Eliminate n/L	0.9853	0.0495
4	Eliminate d/L	0.9919	0.0349
5	Eliminate H/L	0.9961	0.0247

In order to demonstrate comparison of the estimated values by any methods, the results obtained by Chawla et al. [2], numerical model using SEEP/W, ANN and ANN-WOA as an example for the conditions of d/L = 0.0004, n/L= 0.048 and H/L = 1.344 and two states of s/L = 0.24 and 0.32 are presented in Table 7.

Table 7. Estimated results of U_d/U_o for two states s/L=0.24 and s/L=0.32

	s/L=0.24	**s/L=0.32**
Methods	**U_d/U_0**	**U_d/U_0**
Chawla et al. (1990)	0.350	0.391
FEM (SEEP/W)	0.369	0.420
ANN-WOA	0.371	0.414
ANN	0.372	0.411

4. Conclusions

Gravity dams are huge structures and require a large amount of budget obtained from governments. Any attempt that can reduce the total costs in construction of gravity dams, are welcomed from agencies. Control of uplift force in the foundation of gravity dams is an essential factor due for reduction of the dam construction costs. This study deals for control of uplift force using drain pipes in the gravity dams foundation. Guangzhao dam (located in China) was selected because of its accessible design parameters.

A novel machine learning model known as ANN-WOA is proposed in this study for the estimation of total uplift force in gravity dams. Obtained results are compared with that obtained using ANN. The results revealed that both intelligent models (ANN-WOA and ANN) were able to estimate the relative total uplift force with good accuracy. The values of statistical metrics for ANN-WOA model are: R^2 = 0.998, RMSE = 0.021, NSE = 0.989, KGE= 0.964 and RE% = 3.3% while those were 0.980, 0.023, 0.982, 0.953 and 4.67% respectively for ANN model. The results indicate a relatively better performance of ANN-WOA compared to ANN. The data density and violin plots revealed that the dispersion and the probability distribution of the ANN-WOA estimates were able to resemble the results of the numerical simulation more accurately compared to ANN estimates.

A two-dimensional (Plan view) model was developed in this study for the simulation of total uplift force. A three-dimensional model can be developed in future to assess the effect of depth and angle of the drains in reducing the uplift force. The results obtained using the three-dimensional model can be compared with the results obtained using the machine learning models. Besides, other intelligent models can be used in the estimation of relative total uplift force and compare the results with that obtained in the present study using ANN-WOA model. An important challenge in optimization in engineering is the accurate estimation of time-varying changes. Therefore, a model can be developed in future for the evaluation of the changes in uplift force with time.

Notations

The following notations are used in this study:

U_d	Total uplift force with drain (kN/m);
U_O	Total uplift force without drain (kN/m);
H_d	Water head in position of drains (m);
H	Water surface level in reservoir (m);
L	Dam width in bottom (m);
S	Distance of drains from upstream heel (m);
N	Distance center to center of drains (m);
d	Drain diameter (m);
T	Dam length (m);
k_{sat}	Saturated hydraulic conductivity (m/s);
θ	Volumetric water content (m^3/m^3);
h	Total head (m);
Q	Applied boundary flux (1/s);
t	Time (s);
g	Gravity acceleration (m/s^2);
k	Hydraulic conductivity (m/s);
O_i	Obtained value from the FEM (-)
P_i	Estimated value from the intelligence methods (-);
$\bar{O}$	Calculated values average from FEM (-);
$\bar{P}$	Estimated values average from the intelligence models (-);
N	Data number (-);
x , y	Cartesian coordinates

Abbreviations

FEM	Finite Element Method
PDE	Partial Differential Equations
RMSE	Root Mean Square Errors
R^2	Determination Coefficient
RE%	Percent of Relative Error
NSE	Nash-Sutcliffe Efficiency
KGE	Kling-Gupta Efficiency
ANN	Artificial Neural Network
MLP	Multi-Layer Perceptron
WOA	Whale Optimization Algorithm
GA	Genetic Algorithm
LMA	Lewenberg Marquard Algorithm
GEP	Gene Expression Programming
ML	Machine Learning
AI	Artificial Intelligence
SEEP/W	Subgroup of Geo-studio software

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